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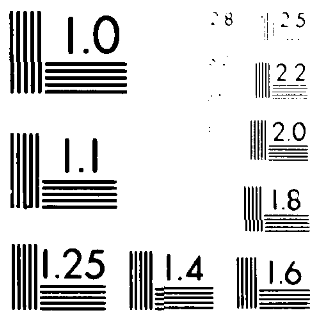

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number) Two new algorithms for Pisarenko's Harmonic Retrieval Method are introduced. These new algorithms — Gradient Type (LMS) and Approximate Deterministic Least-Squares Algorithm — provide faster initial convergence and are able to carry out on line spectrum estimation. Some simulation results are presented.		

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ON THE ADAPTIVE IMPLEMENTATION OF PISARENKO'S HARMONIC RETRIEVAL METHOD+

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AFOSR-TR- 82-0476

SUMMARY

The development of adaptive techniques for estimating the parameters of sinusoidal signals in additive noise is important in many applications. The so-called adaptive line enhancer(ALE) proposed by Widrow et al.[1] has been a popular solution. The ALE is a tapped-delay-line filter of some fixed length, whose tap gains are recursively adjusted by using the so-called LMS[1] algorithm so that they converge to the solution of the normal equations for the one-step minimum mean-square-error prediction problem. Another popular solution uses a so-called ladder or lattice filter whose parameters are adjusted by using a technique, due to Burg[2], based on minimizing the sum of certain forward and backward one-step prediction residuals. Burg's technique is an off-line one. Griffiths[3] merged the above approaches by proposing a lattice filter whose coefficients were adapted by using the LMS algorithm, leading to what is often called a gradient lattice(or ladder) filter.

The above three approaches all yield spectral estimates with fairly sharp peaks but the estimates of the sinusoidal frequencies invariably appear to be biased when the sinusoids are observed in the presence of additive white noise.

In an attempt to improve the above methods with respect to bias, Ulrych and Clayton[4] have proposed a least-squares fitting of an autoregressive model, based on a criterion involving both forward and backward prediction errors but, unlike Burg's method, without using a ladder filter model. With the help of simulation results they have demonstrated that the bias in the spectral estimates can be reduced significantly compared to the Burg technique. It should be noted, though, that this is

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true only for short data lengths, since all the above techniques give identical results for large data lengths.

Possibilities for improvement of the above approaches becomes apparent when one considers that they were all designed to converge to the optimum linear least-squares solution for the prediction of any random process, and do not specifically exploit the fact that the signals are sinusoidal. Pisarenko[5] was perhaps the first to attempt to do this in his so-called "harmonic retrieval" method, which involves determining the minimum eigenvalue and the corresponding eigenvector of the covariance matrix of the observed random process. Thompson[6] noted that this eigenvalue-eigenvector computation was equivalent to a certain constrained gradient-search procedure for obtaining an adaptive version of Pisarenko's method. Thompson's simulations verified that the frequency estimates provided by his procedure were unbiased. However, the main cost of this technique was that the initial convergence rate may be very slow for certain poor "initial conditions".

One of the goals of this paper is to consider a way of providing faster initial convergence by using a different algorithm for the above problem. Restating the constrained minimization as an unconstrained nonlinear problem, we derived the following two adaptive algorithms.

Consider the adaptive filter with constrained coefficients, as suggested by Thompson, shown in Fig.1. The observed process, consisting of a sum of sinusoids and white noise, is denoted by a time series x(k). The filter output e(k) can be expressed as the inner product

$$e(k) = \bar{A}^T X(k) \tag{1}$$

where

$$\bar{A} = [\bar{a}_0, \ldots\ldots\ldots, \bar{a}_{L-1}]^T \tag{2a}$$

$$X(k) = [x(k), x(k-1), \ldots\ldots, x(k-L+1)]^T \tag{2b}$$

and

$$\bar{A} = A / \|A\|$$

is the constrained unit-norm vector. T denotes the matrix transpose.

a. Gradient-Type (LMS) Scheme

The adaptation criterion for the filter of Fig. 1 is

$$J = \tfrac{1}{2} E[e^2(k)] \tag{3}$$

Expressing e(k) in terms of unnormalized weight vector **A**,

$$e(k) = A^T X(k) / \|A\| \tag{4}$$

the gradient estimate at k-th sample instant is

$$\hat{\nabla}_k J = \frac{1}{\|\hat{A}(k-1)\|} \left[e(k)X(k) - e^2(k) \frac{\hat{A}(k-1)}{\|\hat{A}(k-1)\|} \right] \qquad (5)$$

The time update for the normalized i-th coefficient is then given by

$$\hat{\hat{a}}_i(k) = \alpha(k) \left\{ \hat{\hat{a}}_i(k-1) - \mu[e(k)x(k-i) - e^2(k)\hat{\hat{a}}_i(k-1)] \right\} \qquad (6)$$

where $\alpha(k) = \|\hat{A}(k-1)\| / \|\hat{A}(k)\|$

and μ is a positive scalar constant. Equation (6) describes the constrained LMS algorithm.

The stationary points of the above algorithm are given by the equation

$$E\{[X(k) - e(k)\hat{\hat{A}}]\ e(k)\} = 0$$

which, using Eq.(1), can be simplified to give

$$E\{X(k)X^T(k)\}\ \hat{\hat{A}} = \hat{\hat{A}}^T\ E\{X(k)X^T(k)\}\ \hat{\hat{A}}.\hat{\hat{A}}$$

Clearly, every eigenvector of the covariance matrix satisfies this equation. By a somewhat more involved argument it can be shown that only the eigenvector corresponding to the minimum eigenvalue gives a stable stationary point.

b. Approximate Deterministic Least-Squares Algorithm

For an alternative algorithm, we choose the adaptation criterion for the filter of Fig. 1 as the minimization of

$$V = \frac{1}{2} \sum_{s=0}^{t} e^2(s) \qquad (7)$$

with respect to the unit-norm vector $\bar{A}$. Because of the constraint on the weight vector, the minimization of (7) is a nonlinear problem and an exact least-squares solution does not appear to exist. We, therefore, derive an approximate solution using a Gauss-Newton type algorithm.

Once again, expressing e(s) as

$$e(s) = A^T X(s) / \|A\|$$

we obtain

$$\nabla V = \frac{1}{\|A\|} \sum_{s=0}^{t} e(s)[X(s) - \bar{A}e(s)] \qquad (8)$$

and

$$\nabla^2 V \approx \frac{1}{\|A\|^2} \sum_{s=0}^{t} \psi(s)\, \psi^T(s) \qquad (9)$$

where

$$\psi(s) = X(s) - \bar{A}e(s) \tag{10}$$

From (8),(9) and (10), the Gauss-Newton algorithm can be obtained as follows:

$$\hat{A}(k) = \alpha(k)[\hat{A}(k-1) - P(k)\psi(k)e(k)] \tag{11a}$$

$$P(k) = P(k-1) - \frac{P(k-1)\psi(k)\psi^T(k)P(k-1)}{1+\psi^T(k)P(k-1)\psi(k)} \tag{11b}$$

$$\psi(k) = X(k) - \hat{A}(k-1)e(k) \tag{11c}$$

where $\alpha(k)$ is a scalar constant whose value is chosen such that the updated weight vector has unit norm. In practical applications, an exponential weighting with the so-called forgetting factor, λ, is applied to the data so as to track the slowly varying parameters of the data. This weighting reflects in recursion (11b) in two ways. i) The right-hand-side is divided by λ, and ii) unity in the denominator is replaced by λ.

Simulations have been performed to study the properties of the above two schemes. Figures 2 and 3 show the spectral estimates obtained with the two techniques. Two sinusoids of normalized frequencies 0.15 and 0.20 are used in the examples. The most important conclusions that can be drawn from the results are the following.

The least-squares-type algorithm has faster initial convergence. For poor signal-to-noise ratio, both algorithms perform similarly close to the true parameters. The removal of the bias in the frequency estimates is slower than the resolution between different frequencies.

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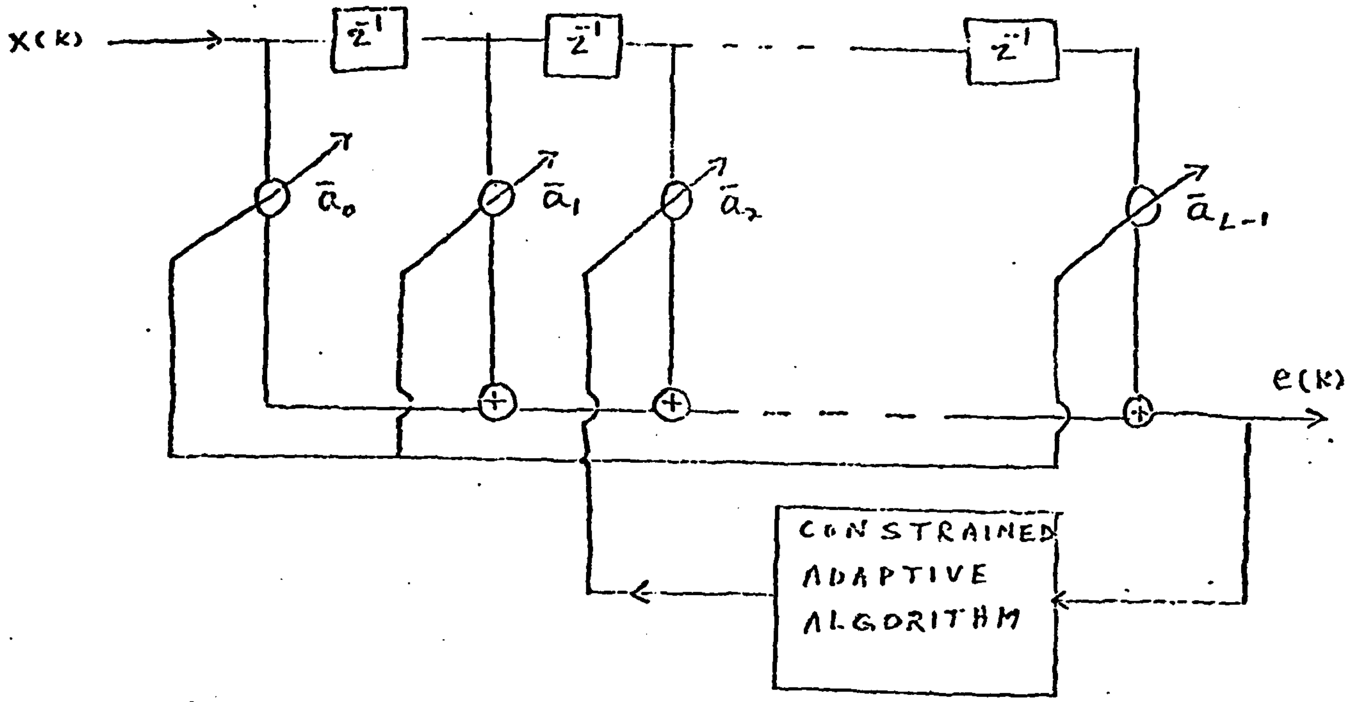
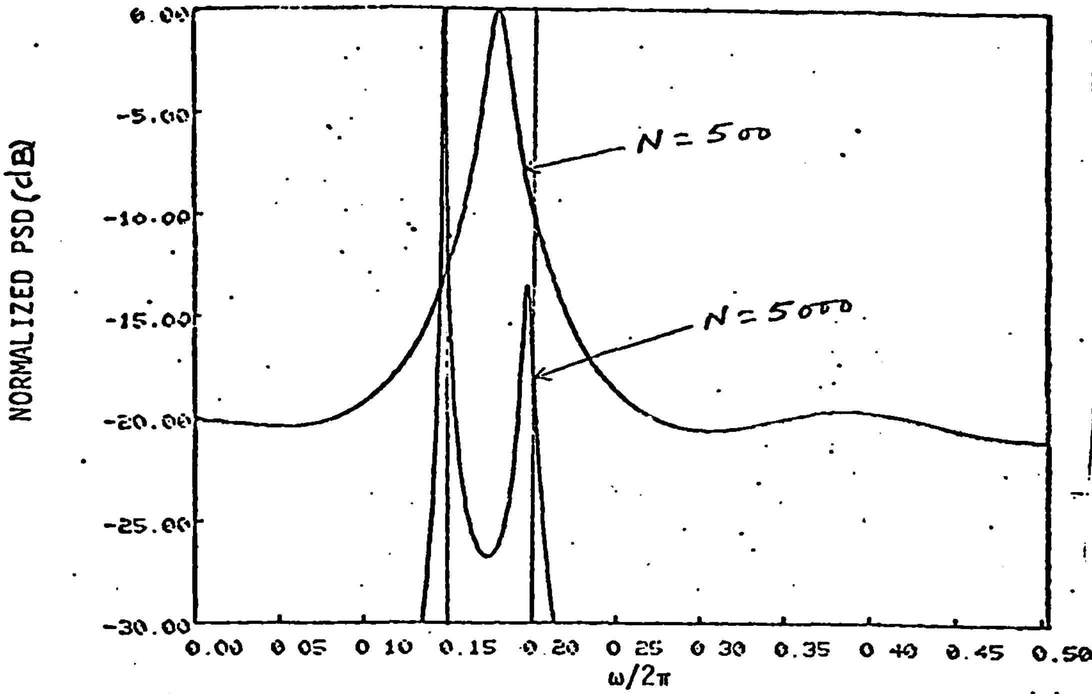
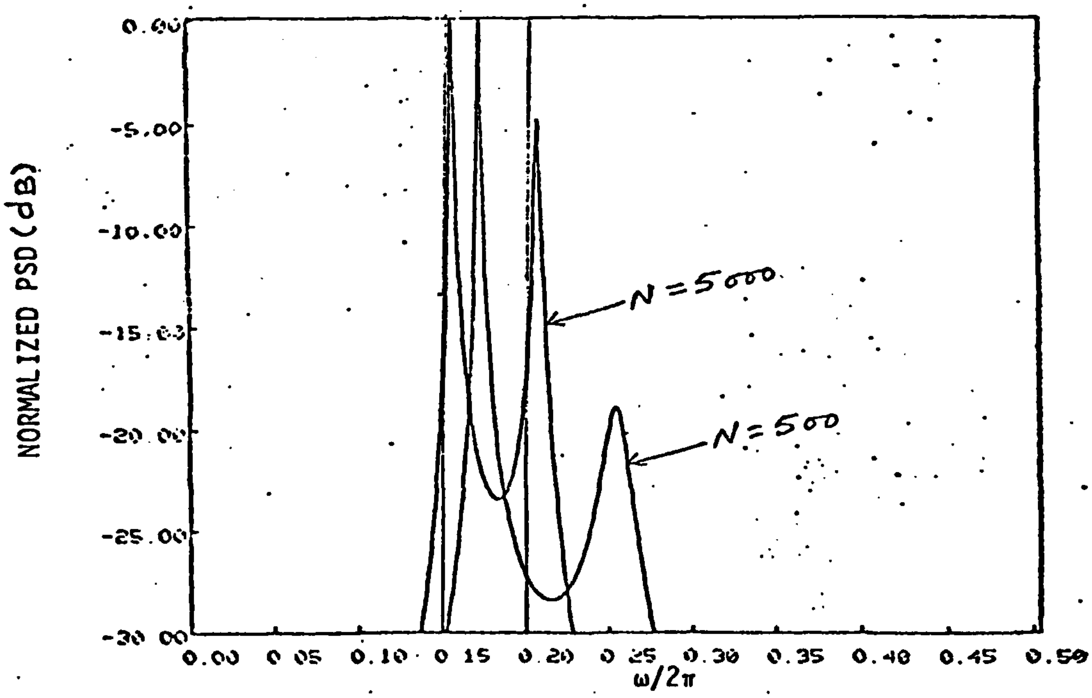


Fig. 1 Constrained AR spectral estimator

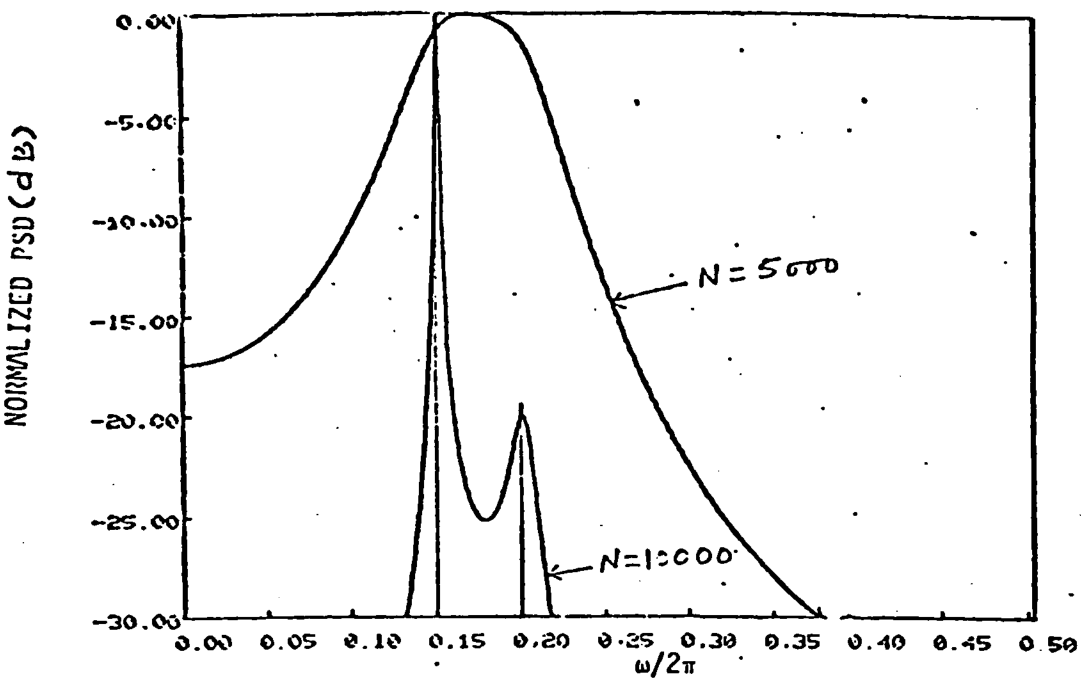


(a) LMS algorithm (μ=0.001)

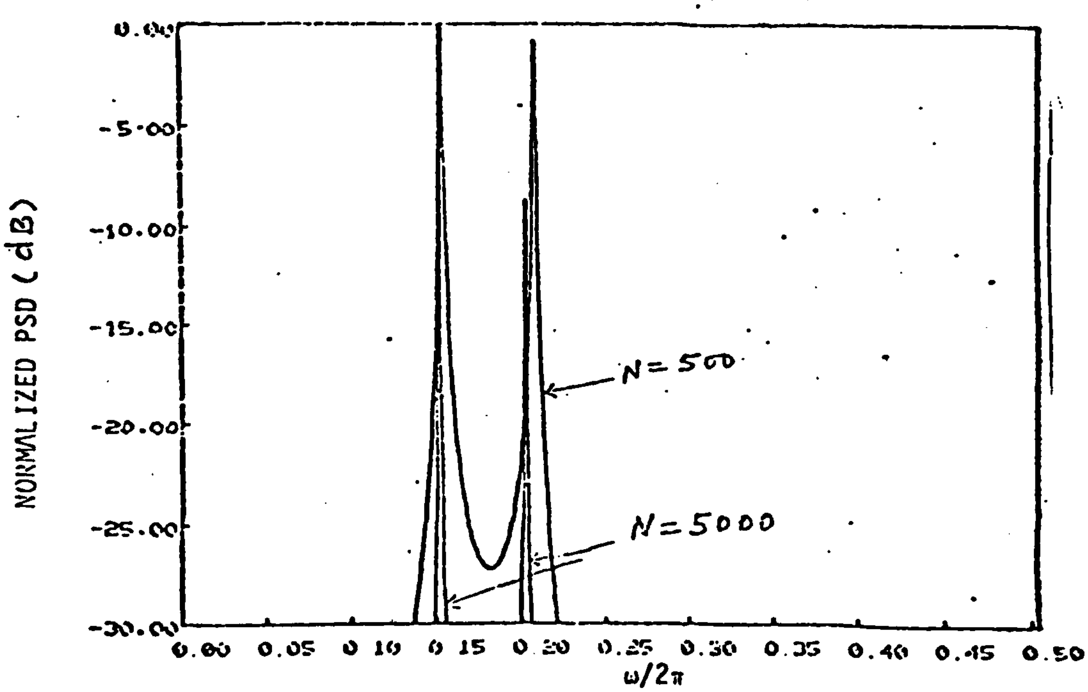


(b) Approximate least-squares algorithm (λ=0.98, P(0)=100)

Fig. 2 Simulated spectral estimates (SNR=0 dB, L=7)



(a) LMS algorithm (μ=0.001)



(b) Approximate least-squares algorithm (λ=0.98, P(0)=100)

Fig. 3 Simulated spectral estimates (SNR=12 dB, L=5)

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